RESULTS AND IMPLICATIONS OF NEURAL NETWORK RETRIEVALS OF SATELLITE TEMPERATURE SOUNDINGS

Donald Bustamante[1], James Cogan[2],
William Gutman[1], Edward Measure*, and Gail Vaucher[2]

ABSTRACT

Back propagation neural networks were used to retrieve atmospheric temperature profiles from meteorological satellite sounder radiances. The networks were trained in TIROS Operational Vertical Sounder (TOVS) data collected during 1992 and 1993 over the United States and Canada. The truth sets for training and testing the neural networks consisted of data from the University of Wisconsin's TOVS Export Package and near-to-coincident rawinsonde data. The retrievals had a root-mean-square (RMS) error over mandatory levels (1000 to 10 hPa) of< 3.5 K for the complete set of data. For a subset consisting of data from the Southeastern United States, the error dropped to< 2.5 K over most levels (i.e. not near the surface and tropopause).

These studies demonstrate that neural networks can provide reasonable results using only the TOVS infrared (HIRS/2) sounding channels. Inclusion of the MSU radiances led to a small improvement. A sensitivity analysis identified ten HIRS/2 channels as the most significant input. A "reduced" net using only those ten channels produced results that suggest a "degradation" of only 0.2 or 0.3 K relative to the full net. The potential significance of these results is discussed.

Recently, the neural network methodology has been applied to infrared sounder data obtained with GOES I-M sounders carried aboard current generation Geostationary Operational Environmental Satellites (GOES). Comparable or better levels of accuracy have been obtained with GOES retrievals. These results are also discussed.

1. RETRIEVAL APPROACHES

Following Houghton (1985), for a cloudless atmosphere, the radiance of the earth's atmosphere as measured by a satellite-borne radiometer may be expressed as

$$I(\upsilon) = B(\upsilon, T_s)\tau(\upsilon, p_s) - \int_{x(0)}^{x(p_s)} B(\upsilon, p)\frac{d\tau(\upsilon, p)}{dx(p)}\,dx(p)$$

where $I(v)$ is the radiance at wavenumber v; $B(\upsilon, T)$ *is* the Planck radiance at wavenumber v and surface temperature T_s; τ *is* the atmospheric fractional transmittance from a given pressure level to the top of the atmosphere; $x(p)$ is a function of pressure, usually in p. The first term represents the

[1] Author is with the Physical Science Laboratory, New Mexico State University, Las Cruces, New Mexico 88003.

[2] Author is with the Information Sciences and Technology Directorate, Army Research Laboratory, White Sands Missile Range, New Mexico 88002.

spectral radiance emitted by the surface and attenuated by the atmosphere; the second term represents the radiance emitted by the atmosphere.

Correcting for surface contributions, the equation becomes

$$I_\upsilon(\upsilon) = \varepsilon_\upsilon B_\upsilon(T_s)\tau(0,p_s) + \int_0^{p_s} B(T)W_\upsilon(p)\frac{dp}{p}$$

$$W_\upsilon(p) = -\left\{1-(1-\varepsilon_\upsilon)\left[\frac{\tau_\upsilon(0,p_s)}{\tau_\upsilon(0,p)}\right]^2\right\}\frac{\partial\tau_\upsilon(0,p)}{\partial\ln p}$$

where ε is the emissivity, and W is the Planck weighting function. The term

$$\frac{\partial\tau_\upsilon(0,p)}{\partial\ln p}$$

is referred to as the sensor weighting function. These weighting functions are specific for each channel of a sounding instrument such as the TOVS or GOES Sounder, and vary with p. In the infrared region covered by most sounder channels instrumentation, ε is approximately unity. Although the forward equation is easily solved, the inverse is ill-posed; small changes in I result in large errors in T. There is no unique solution, since the contribution to the radiances observed by the satellite arise from deep within the atmosphere and the sensor channels are not spatially independent (Houghton, 1985).

1.1 Conventional Retrieval Approaches

Conventional approaches utilize additional data to regularize the problem and obtain a solution. These additional data include ***in-situ*** rawinsonde observations and statistics of atmospheric structure, pattern recognition (to match a rawinsonde profile with an initial guess profile), and the use of Numerical Weather Prediction (NWP) model output to condition the retrieval. Mathematically, these approaches involve the use of linear and non-linear techniques. Linear techniques such as linearization, basis functions, least squares regression, statistical regularization, and minimal information approaches have been used. Non-linear approaches typically involve an iterative form of solution. Detailed reviews can be found in Rodgers (1976) and Deepak, *et al.* (1988). The conventional algorithm used in this study was the TOVS Export Package (TEP) developed by the University of Wisconsin (Smith, *et al.*, 1983).

1.2 Neural Network Retrieval Approaches

The application of neural networks to the retrieval of atmospheric temperature profiles has been studied by several researchers, who have used a variety of data and data sources in their studies. Bustamante *et al.* (1996a) provide a brief description of some of this work. The effort reported here is based on work that has been reported previously by Bustamante *et al.* (1992, 1993, 1994a, 1996a, 1996b).

2. TIROS AND TOVS

The TIROS satellites are near-polar orbiting satellites operated by the National Environmental Satellite Service of the National Oceanic and Atmospheric Administration (NOAA). These satellites provide data used for meteorological prediction and warning, oceanographic and hydrologic data and space environment sensing (Schwalb, 1982). The satellites are equipped with environmental sensors that include the TIROS Operational Vertical Sounder (TOVS).

The TOVS instrumentation consists of the High Resolution Infrared Radiation Sensor (HIRS/2), the Stratospheric Sounding Unit (SSU), and the Microwave Sounding Unit (MSU). The HIRS/2 is a 20 channel sensor, primarily infrared, which is used for obtaining vertical temperature profiles, atmospheric water content, and ozone measurements. The S SU is a 3 channel sensor which measures the radiation emitted by carbon dioxide in the stratosphere. The MSU is a 4 channel Dicke radiometer which measures the 5.5 mm oxygen band. Detailed specifications on scan spot size, swath width, and other sounding parameters may be found in Schwalb (1982) and Barnes and Smallwood (1982).

2.1.1 Data

Data were collected by the U. S. Army Research Laboratory's Information Science& Technology Directorate (ARL/IS&TD) using SeaSpace TerraScan hardware and software. Data from the satellite passfiles were processed to yield radiance values for the TOVS sensor channels. Additional information such as site elevation, latitude, longitude, satellite zenith angle, solar zenith angle, and solar phase angle were computed and appended to the datasets.

At the ARL/IS&TD site only the HIRS/2 radiances were collected. The present study had access to 19 of 20 HIRS/2 data channels. Data were available for time periods in 1992 and 1993. TOVS HIRS/2 data for the United States and Canada were collected by the ARL/IS&TD TerraScan system. Additional TOVS radiance data, which included MSU and S SU, were obtained from Louisiana State University's Coastal Studies Institute (Southeastern United States). The SeaSpace system uses the TEP to retrieve atmospheric profiles of temperature and moisture.

National Weather Service (NWS) rawinsonde observational (RAOB) data for North America were provided by the ARL/IS&TD Upper Air Database and NOAA's National Climatic Data Center (NCDC). The data were selected to cover the time period July 1992–August 1993. These data were also used as truth in the training of the networks. For ease in handling, these data were partitioned into geographical sectors covering half month periods.

RAOBS are typically taken at 0000 UTC and 1200 UTC. By convention, the geographic . coordinates of the release point are used, and a vertical rise is assumed. Satellite coverage of the geographic region of interest occurs when the satellite passes over that region, The TIROS orbital period is approximately 102 minutes, resulting in 14.1 orbits per day. Since the TIROS satellites are near-polar orbiters, the geographic coverage on subsequent passes is not identical; a two satellite configuration can pass over the same location approximately every 5 hours (average value; more often near the poles).

TOVS radiance data were spatio-temporally matched with RAOBS. The matching program permitted user specification of latitude, longitude, and time windows. Spatio-temporal criteria used are based on the satellite observation. A spatial separation of ±0.5 degree was used for latitude and longitude, and observations taken within 1.5 hours before and 2.0 hours following the satellite observation were considered to be matched.

Feed-forward backpropagation networks were created using Neural Ware's Neural Works Professional II neural network development environment running on an HP 9000/735 workstation. The initial network utilized HIRS/2 Channels 1 through 19, latitude, longitude, satellite zenith angle, solar zenith angle, scatter phase angle, sun reflection angle, and elevation as inputs. Other networks were tested that used combinations of HIRS/2 and MSU channels and differences and ratios between various channels. The output nodes for all networks consisted of the temperatures at the meteorological mandatory levels (1000, 850, 700, 500, 400, 300, 250, 200, 150, 100, 70, 50, 30, 20, and 10 mb) and at the surface.

The networks were instrumented to record the root-mean-square (RMS) error of the network during training using the following equation:

$$RMS = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(O_i - T_i)^2\right)}$$

where ***n* is** the number of thermal profiles derived, O_i is the *i*-th output of the neural network, and T_i is the *i*-th "truth value. The networks were trained until the RMS error was minimized. This typically occurred at 15,000 training iterations. The final RMS error at the completion of training was 0.02. This RMS value is the overall value for all output nodes.

Various neural network retrievals were performed with the data. Both rawinsondes and conventionally retrieved profiles (using the TEP) were used as truth. The training and testing were performed using data collected between September 1 and October 15, 1992. The RMS error as a function of mandatory level is shown if Figure 1 for a case using rawinsonde data as truth. Typical RMS error values are 3-4 K. The sensitivity of the RMS error to the number of nodes in the single hidden layer was investigated by training and testing networks with various numbers of nodes. As seen in Figure 2, this analysis demonstrates that ten nodes is the optimum number.

An important aspect of the investigation was a sensitivity analysis to determine whether any of the HIRS/2 channels could be omitted from the network. In fact, a network utilizing only HIRS/2 channels 1, 3, 4, 7, 12, 13, 14, 16, 17, and 19 was found to yield results comparable to those from the full network. The RMS error of the reduced network is somewhat greater at the surface. It is within 0.5 K at 500 mb, and it is actually smaller than that of the fill network at the tropopause. . This suggests that a simpler, less expensive sensor suite could be used on future satellites without significant loss of temperature retrieval accuracy.

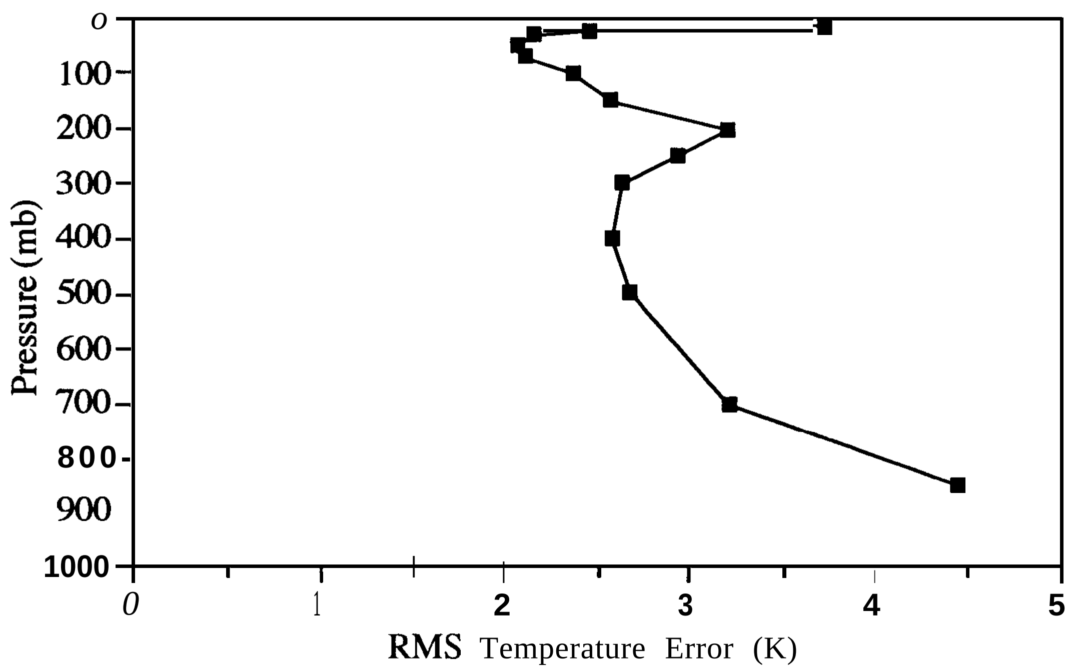

Figure 1. RMS temperature retrieval error as a function of atmospheric level for a neural network trained and tested with TOVS data using rawinsonde data as truth.

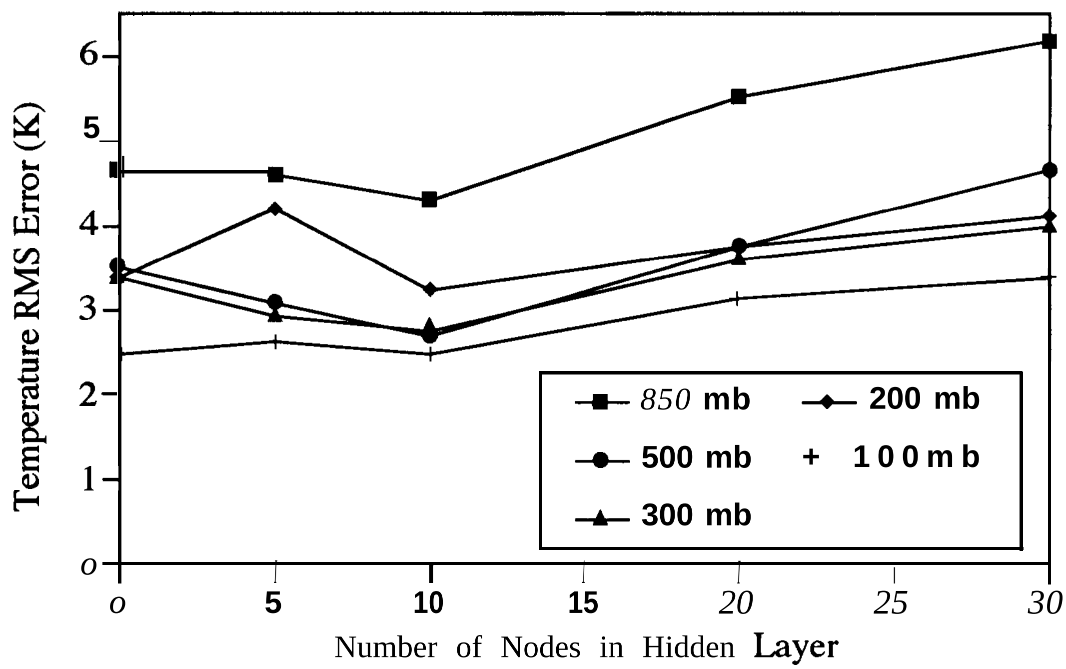

Figure 2. TOVS RMS temperature retrieval error as a function of number of nodes in the hidden layer of the neural network. Ten nodes is the optimum number.

3. GOES AND GOES I-M SOUNDERS

The most recent work extends the neural network retrieval methodology to atmospheric sounder data sets obtained from geosynchronous satellites. Geosynchronous satellites provide the obvious benefit that most of the earth facing the satellite is continuously within view of the sensors. The Geostationary Operational Environmental Satellites (GOES) provide high resolution visible and infrared imagery and multiband infrared soundings. Currently, there are 2 operational GOES platforms, GOES 8, and GOES 9. These satellites are also called GOES East and Goes West because they are stationed at longitudes 75° W and 135° W respectively. Both are from the GOES I-M series that incorporates significant improvements over earlier designs. One of the instruments carried aboard is the GOES I-M sounder. This is a multiband, high spatial resolution radiometer. The GOES I-M sounder is similar to the HIRS/2 instrument of the TOVS package. The eighteen infrared channels have similar center frequencies and bandwidths, and similar applicability to retrieval of atmospheric parameters.

Ten GOES data sets were obtained through the National Climatic Data Center. These data corresponded in time to the 0000 and 1200 UTC rawinsonde launches over a five day period from November 8–1 2, 1994. Corresponding rawinsonde data were taken from ***Rawinsonde Data of North America, Volume IV, 1990–1994 (Updated)*** published by the National Climatic Data Center. The actual GOES infrared data acquisition times were 1146 and 2346 UTC each day. All rawinsonde launch times were within 0.8 hour of the GOES data acquisition, and most were within 0.6 hour. GOES infrared sounder data were extracted from the distribution data files using the University of Wisconsin's MCIDAS software product. Spatial reference information for the GOES infrared pixels was used to assemble neural network training and testing files. Raw infrared radiance values were used rather than derived brightness temperatures. Any pixel for which all eighteen sounder channels were valid and which was within 0.5 degree in both latitude and longitude of the corresponding rawinsonde launch point was used. Because of the curvature of the earth, the latitude and longitude spacing of the pixels is a function of position, so the number of pixels that could be used with each rawinsonde varied.

The temperatures at the 850, 700, 500, 400, 300, 250, 200, 150, and 100 mb mandatory levels as well as the surface temperatures were used to train and test the neural networks. These levels were consistently available in the rawinsonde database. Nevertheless, a large fraction of the data could not be used because of missing levels. In total, over 14,000 training/testing vectors were assembled from the rawinsonde and infrared sounder data. These vectors were randomly partitioned into two approximately equal size files. One file was used for training, and the other was used for testing.

RMS errors associated with the extraction were computed by comparing rawinsonde . temperatures with temperatures retrieved from the testing set. The RMS errors are plotted as a function of level in Figure 3. Numerous variations of neural network architecture were tested. In all cases, a single hidden node was used, but the number of nodes in the hidden layer was varied from 5 to 25. Consistent with the findings from the TOVS retrieval (Bustamante, *et al.*, 1996b), the RMS errors were minimized with 10 hidden nodes, although as seen in Figure 4, the GOES Sounder retrievals exhibited much less sensitivity to this parameter than did the TOVS retrieval.

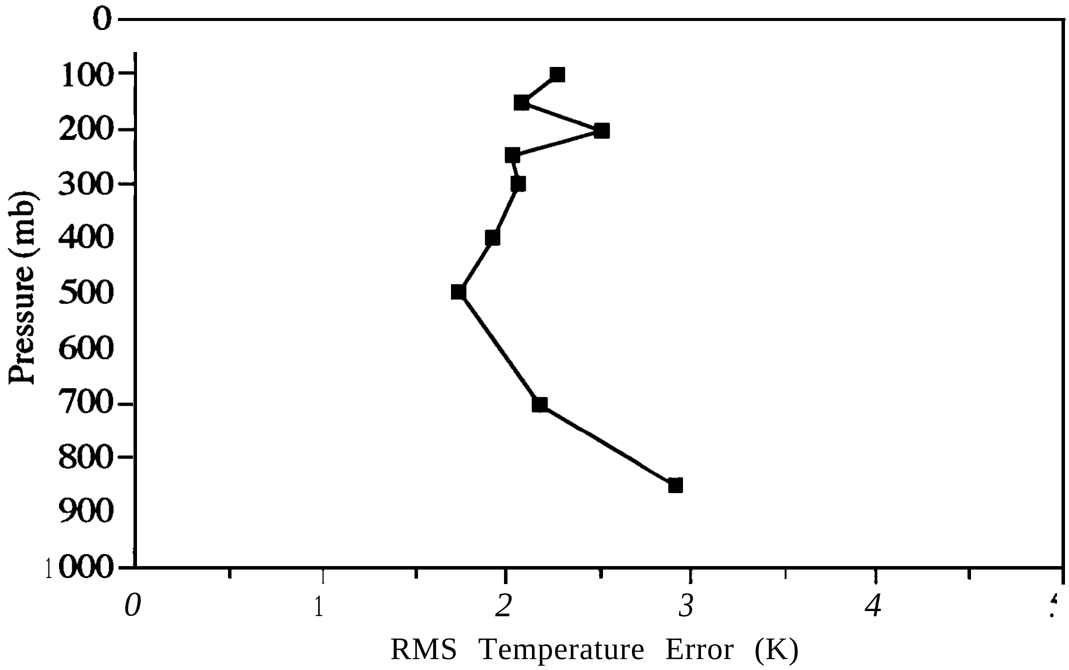

Figure 3. RMS temperature retrieval error as a function of atmospheric level for a neural network trained and tested with GOES Sounder data using rawinsonde data as truth.

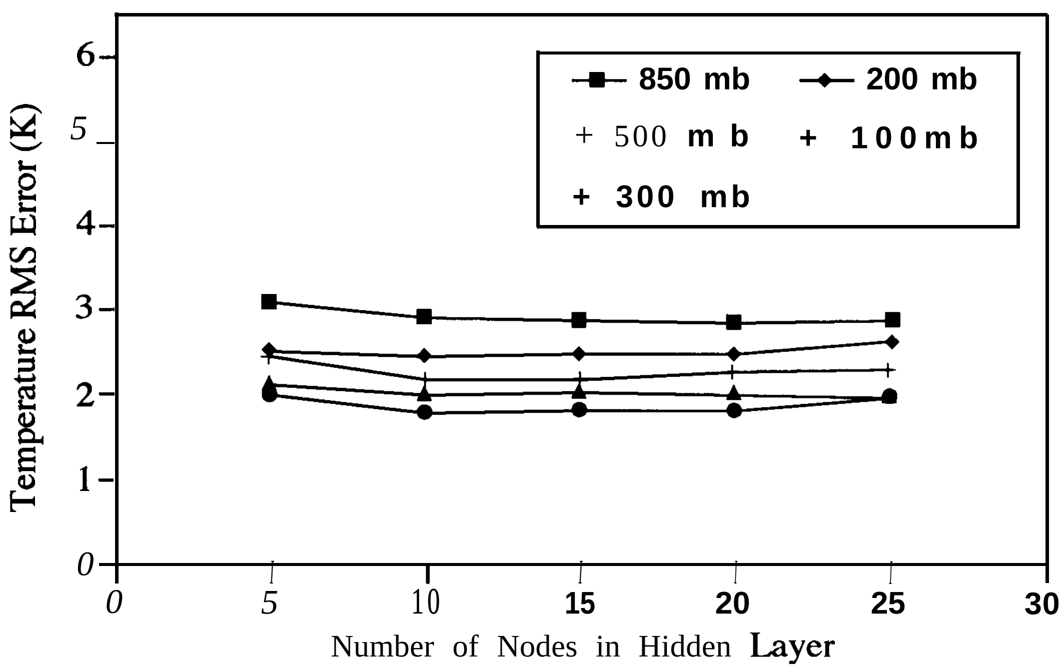

Figure 4. GOES Sounder RMS temperature retrieval error as a function of number of nodes in the hidden layer of the neural network. Ten nodes is the optimum number.

Other network details were also varied. The RMS errors were relatively insensitive to details such as the learning rule and transfer function. The RMS error was < 4 K at the surface and < 3 K at 850 mb. Between 700 and 100 mb, the errors ranged from< 2 K to approximately 2.5 K near the tropopause. These results are somewhat better than those obtained from the TOVS data. In part, this may be because the temporal matching with the rawinsonde data was significantly better. It is noteworthy that the results from both TOVS and GOES data were obtained without the use of a technique for removal of cloud "contamination." In fact, the addition of input to the net in the form of the radiance ratios and differences used in standard "cloud removal" techniques did not noticeably improve the results (Bustamante, ***et al.***, 1996a, 1996b). Nevertheless, inclusion of an effective means to significantly reduce the effect of clouds in the field of view, either by pre-processing or within the net input, should lead to better accuracies.

4. FUTURE DIRECTIONS

Our efforts to date have shown the potential utility of neural net methods for retrieval of temperature soundings from meteorological satellite radiances. Further work on refining the method for GOES data should lead to further improvement to the already promising results, and to a more generalized neural network or set of networks where a net is derived for each climate region (Bustamante, *et al.*, 1996a). Extension of the work using polar orbiter data to the microwave sounder (Special Sensor Microwave/Temperature, SSM/T) on the Defense Meteorological Satellite Program (DMSP) satellite has the potential to improve accuracy through the ability to more easily remove cloud "contaminated" radiance profiles. Work by Butler *et al.* (1996) indicated the high accuracy possible with SSM/T data. Also, we plan to develop neural networks for retrieval of dewpoint profiles.

In spite of the progress made herein and elsewhere on retrieval of temperature and humidity profiles from satellite data, extraction of reasonably accurate wind velocity soundings remains out of reach. For most applications average wind speed accuracies of around 8 to 10 ins-l from current techniques (Cogan, ***et al.***, 1997) are not adequate. Wind direction errors may reach 900 (Jedlovec, 1985) as a result of errors in gradient of geopotential height. Current methods derive winds from geopotential height gradients using, for example, the geostrophic or gradient wind assumption, which in turn are estimated from temperature soundings and surface information (e.g., surface pressure). Cloud tracking is too uncertain and large scale for many applications. However, a neural network approach may allow one to go directly from radiance gradients to wind velocity or wind velocity components. We plan to test the feasibility of such an approach using the data on hand. If the method shows sufficient potential, we will concentrate our efforts on devising an appropriate neural network or set of networks for extracting wind "directly" from satellite sounder radiances.

5. CONCLUSION

We have developed neural networks for retrieval of temperature soundings from radiances gathered by atmospheric sounders on meteorological satellites. Work to date suggests the potential for accuracies equal or somewhat better than that of current methods. The ability to obtain profiles of nearly the same accuracy relative to rawinsondes from a reduced set of sounder radiances opens the possibility for simpler, less expensive, instruments. Since the method does not use ***a priori*** information once the net is trained, retrieval of temperature profiles requires fewer computer resources and should produce soundings more rapidly than present techniques. The need for smaller, less expensive, processors and the ability to generate numerous soundings in a relatively short time should make satellite temperature soundings more amenable for a variety of applications. Future work in this area may lead to an operationally capable retrieval package that produces temperature profiles with noticeably upgraded accuracy. Further work may determine the feasibility of deriving wind velocities "directly" from satellite sounder radiances. Potentially, neural network methods may lead to the ability to extract wind profiles that are sufficiently accurate for quantitative uses, such as input to mesoscale models.

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